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Issues and Considerations regarding Sharable Data Sets for Recommender Systems in Technology Enhanced Learning

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Abstract

This paper raises the issue of missing data sets for recommender systems in Technology Enhanced Learning that can be used as benchmarks to compare different recommendation approaches. It discusses how suitable data sets could be created according to some initial suggestions, and investigates a number of steps that may be followed in order to develop reference data sets that will be adopted and reused within a scientific community. In addition, policies are discussed that are needed to enhance sharing of data sets by taking into account legal protection rights. Finally, an initial elaboration of a representation and exchange format for sharable TEL data sets is carried out. The paper concludes with future research needs.

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1. Introduction

Personalisation is a key approach to overcome the plethora of information in the knowledge society. It is expected that personalised learning has the potential to reduce delivery costs, to create more effective learning environments and experiences, to accelerate time to competence development, and to increase collaboration between learners. Recommender systems are one of the promising technologies to support people in finding the most suitable information and peer learners. They are increasingly being applied in Technology-Enhanced Learning (TEL) in various European projects (e.g., TENCompetence^a, OpenScout^b, APOSDLE^c, ROLE^d, STELLAR^e, Organic.Edunet^f, VOA3R^g) in order to personalise learning content and connect suitable peer learners according to their context (individual needs, preferences, and learning goals). In the world of consumer recommender systems, it is a common practice to use different data sets with specific characteristics to evaluate new recommender system algorithms. Several data sets have already been released publicly, such as the MovieLens, BookCrossing, and EachMovie data sets. These data sets serve as common benchmarks to evaluate new recommendation algorithms like in O'Sullivan et al. [2] and Sarwar et al. [3].

Data sets for TEL are many-folded as TEL takes place in the whole spectrum of learning roughly distinguished between formal and non-formal learning settings. Both settings offer a rather different context that has to be taken into account by recommender systems in order to offer personalised information to individual learners. Formal learning is usually organised according to some curriculum and traditionally occurs in teacher-directed environments with person-to-person interactions. Non-formal learning mainly takes place in learning phases of lifelong learners who are not participating in any formal learning context. They are acting more self-directed and they are responsible for their own learning pace and path. Learning content for non-formal learning becomes more and more available through different Web 2.0 sources like blogs, social bookmarking tools such as Delicious, or document sharing platforms like Scribd or Slideshare.

Between both ends of the spectrum various overlapping learning settings have been identified, such as workplace learning, as described by Lindstaedt et al. [4], and informal learning. From the perspective of a recommender system each learning setting has its own characteristic data sets, user models, recommendation tasks, and most suitable recommendation algorithms.

So far, no data sets have been made publicly available for formal learning, non-formal learning, or anything in between. Therefore, the performance results of different research efforts into recommender systems are hardly comparable according to Manouselis et al. [5]. There is no universally valid knowledge about which recommender system algorithm can be applied successfully in a certain learning setting. Drawing conclusions about the validity and generalisability of scientific experiments depends on the possibility of verification, repeatability, and comparisons of results. Thus, a collection of publicly available data sets is needed to address the different learning settings. Such a collection would enable researchers to create repeatable experiments to gain valid and comprehensive knowledge about how certain recommender system algorithms performed on a certain data set and in certain learning settings.

Therefore, we propose in this paper to assemble and collect publicly available data sets for recommender systems in TEL. The two main objectives of a data set collection will be (1) to assemble data sets from different TEL research fields, and (2) to track the outcomes of applied recommender system algorithms on these data sets. Various additional challenges have to be solved in order to create data set-driven research within TEL. In Section 2, we present three guidelines that help researchers to select suitable TEL data sources for particular learning settings. Section 3 elaborates how the selected data sources should be assembled into a data set. In Section 4, we focus on policies that are needed to enhance sharing of data sets for TEL by taking into account legal protection rights. Afterwards, in Section 5, we propose a first format for exchanging data sets that includes a common metadata

^a <http://tencomptence.org>

^b <http://www.openscout.net/>

^c <http://www.aposdle.tugraz.at/>

^d <http://www.role-project.eu>

^e <http://stellarnet.eu>

^f <http://portal.organic-edunet.eu/>

^g <http://voa3r.eu/>

structure to enable the access to and interpretation of data sets. Finally, we conclude the paper with future research questions that have not been answered sufficiently so far.

2. Guidelines for assembling suitable data sets

The *GroupLens* research group explicitly discussed the challenges of creating and using data sets specifically for testing recommender algorithms in Herlocker et al. [6]. They emphasised that it is very important that the recommendation task the algorithm is designed for needs to be similar to the tasks supported by the system from which the data was collected. An example is the MovieLens recommender system, which offers support for the *Find Good items* user task. This means that the recommender system tends to show those items that are very popular because it has more ratings about them. As a consequence, the MovieLens data set has fewer ratings for unpopular movies. Therefore, using this data set to evaluate a different task such as *Recommend Sequence* or *Annotation in Context* would be inappropriate. In Manouselis et al. [7], a comprehensive overview of recommendation tasks for TEL recommender systems is given. These recommendation tasks could be further allocated to different learning settings that are possible for TEL recommender systems.

Thus, data sets with realistic representations of the recommendation task and the learning setting are needed in order to evaluate recommendation algorithms with particular recommendation tasks. For instance, learning settings could be data sets from Moodle instances running in schools or universities (formal learning), data sets from professional communities like meeting recordings (Flashmeeting data in Wild et al. [8]), repositories of research articles (Google Scholar, EC-TEL proceedings, Mendeley, CiteULike, ResearchIndex), or collected Web 2.0 contributions of Mashup environments, such as ReMashed in Drachsler et al. [9] or TeamSpace in Glahn et al. [10].

We identified three guidelines for creating suitable data sets for TEL recommender systems. Following these guidelines may support system developers and researchers to create their most suitable data set and make it reusable for other researchers.

1. *Create a data set that realistically reflects the variables of the learning setting.* It is important to use a data set that is realistic and representative of the target learning setting. In case a recommender system should support ad hoc online communities, the data set also needs to represent these ad hoc communities in terms of the amount of users, items, and type of resources. A good data set includes and stores information that corresponds to the actual content and user interaction in a given learning setting.
2. *Use a sufficiently large set of user profiles.* The success of recommender systems often relies on the availability of a sufficiently large set of users providing a sufficiently large set of ratings. If real data are not available (e.g., if a new system is being developed) then try to use data from similar application contexts or synthetic/simulated data sets that mimic the properties of the targeted one, as Manouselis and Costopoulou describe in [11].
3. *Create data sets that are comparable to others.* Using a data set from a particular TEL project does not mean that the results are generalisable to a certain learning setting. Therefore, it makes sense to create data sets that are structured in a way similar to the one of other data sets especially from the same learning settings. A similar structure enables other researchers to test their recommender system and its algorithms on the same data.

These guidelines should not be seen as limitations. They should encourage researchers to select the most suitable data sets even when they have never been used before for recommender systems. They also should not limit the research to only one recommendation task, because especially hybrid recommender systems can deal with multiple recommendation tasks. In general, learning is a highly individual and human-driven task. Publicly available data sets for various learning settings could be helpfully to evaluate the quality and level of the support that recommender systems can provide the learners with.

3. General approach for creating sharable data sets

Several steps have to be taken to move from the simple notion of using Web 2.0 data in recommendation experiments to producing and sharing actual benchmark data sets with the scientific community. In this section, we list what we believe are some of the most important steps to ensure the quality of a data set. We divide these steps into three different phases: (1) collection, (2) processing, and (3) sharing.

While the *collection phase* is often rushed, gathering Web 2.0 data from a website for use in recommendation experiments is not simply a matter of pointing a crawler to the website in question and pressing a button. The first decision to be made is which source(s) to select. This naturally depends on the purpose and application domain of the recommender system, but even websites within the same domain can provide different functionality and information. For example, many different social bookmarking websites exist, such as Delicious, Furl, Simpy, and Diigo just to name a few. While they all share the same goal—making it easier for users to bookmark valuable websites and information—they all differ in how they exactly provide this service. It is therefore important to carefully analyse the available websites to determine what information is available, if it is suitable for the learning setting, and whether it could be used for generating recommendations.

In addition, Web 2.0 websites can also differ widely in size and characteristics of their user base and in their demographic makeup. Web 2.0 websites in particular tend to attract younger and technology-minded people, whereas a data set of a distance education institute tends to represent older, less technology-savvy people. But different websites might attract different subcultures, which is especially common on Web 2.0 websites. While these characteristics are perhaps not always public knowledge and therefore not always within the experimental control of the researcher, they can influence different aspects of the recommendation experiments and are therefore important to keep in mind. It is advisable to collect multiple data sets from different sources to improve the generalisability of the results.

After these decisions have been made, it is essential to think about how to ensure the representativeness of the data to be collected. Web 2.0 websites, especially the popular ones, are a massive, moving target, which makes it practically impossible to collect all information available on such a website. It is therefore important that the data collected is a representative sample of the user population of the website and of its general usage. For instance, when crawling a social bookmarking website, care has to be taken to not simply start crawling the list of most popular tags, and then collecting all users and items that have been used or have been annotated with those tags. Popular tags are more likely to be linked to popular items and users with large profiles, which would then make up a disproportionately large part of a data set. If the goal is instead to collect a representative sample of all types of users, instead of the most active ones, it is often better to guide the collection process in a different way. For instance, one could rank all users by the profile size, take the logarithm of that size, and divide the users into ten equally-sized groups. By randomly selecting the same number of users from each group, new or less active users have a greater chance of being selected. According to Henzinger et al. [12] techniques from other fields such as index size estimation for search engines could also be used here to ensure the quality of the sampled data.

Finally, before the final collection process takes place, it is advisable to contact the Web 2.0 website directly and see if they are willing to share their data. This saves time for the researcher and bandwidth for the website. Examples of Web 2.0 websites that freely share part of their data include CiteULike, LibraryThing, Last.FM, and Filmtipset.se.

After the initial data sample has been collected, it will have to be *processed*. This can involve a number of different pre-processing steps (cleaning and filtering the data). One likely problem with collected data from non-formal learning settings is that it contains spam. Any system that relies on user-generated content is vulnerable to spam, and Web 2.0 sources are no exception. One of the simplest possible solutions to dealing with spam could be to rank all users by their profile size and automatically disregard the top 5-10% as spam users. However, a more fine-grained approach might be better. Krause et al. [13] present an overview of many different approaches to dealing with spam in social bookmarking websites and can serve as a good starting point for spam detection.

Another issue with collecting data from a Web 2.0 website are duplicates. The ideal scenario would be that every time a user adds some content to a Web 2.0 website, the system can detect whether or not that resource has already been added to the system. While most Web 2.0 services will attempt to match identical content, no matching system can be perfect. Compared to spam, this is obviously less an issue of malicious intent, and more one of carelessness or lack of awareness. However, the presence of duplicates can still affect the algorithms that operate on the data set.

For instance, a recommender system might recommend two versions of the same resource in the same session, or would perhaps not be able to locate all interesting content when the popularity counts are diluted and fragmented. Duplicate detection has mostly been studied as the problem of ‘record linkage’ in databases [14], with the only known application to Web 2.0 websites by Bogers [15].

A third issue related to processing the data set is that of noise reduction. It is common practice in research on recommender systems to filter data sets on noise, as spurious connections between users and items could make it difficult for a recommender system to generate meaningful suggestions. A popular filtering threshold, for instance, is to filter out all users with less than twenty items in their profile. Another possibility could be to view the user-item patterns as a bipartite network and take the k -core of this network, i.e., retain only those users that have at least k items and only those items that were added by at least k users like Seidman in [16]. Whichever filtering regime is used, it is advisable to retain both the unfiltered version of the data set as well as the filtered version, so future users can implement their own filtering scheme.

The third and final phase involves *sharing* the experimental results and the Web 2.0 data set. Besides privacy rules (see Section 4) some attention should also be paid to the way the data is formatted to be shared within a scientific community. In principle, the choice of representation format is completely free, apart from being bound by the specific input requirements of the recommender system. However, for sharing purposes it is prudent to stick to a common representation format that is accepted by open-source recommendation software. As of yet there are no widely accepted representation formats available, but an inspection of the available data sets, such as MovieLens, BookCrossing, and Netflix, could serve as inspiration here. Large amounts of item metadata could be represented in XML format, while another option is making a database dump directly available, as was done in the 2008 ECML/PKDD Discovery Challenge [17].

4. Policies for privacy and legal protection rights

Privacy and legal protection rights are a challenging and rather important topic when talking about sharing of data sets. Finding the right balance between private data and publicly available data is a moving target. The most prominent incident with this respect was the public release of an AOL data set with over 20 million web queries from 650,000 AOL users. The data includes all searches from those users for over three months, as well as whether they clicked on a search result and what that search result was. It definitely is an inspiring data set for researchers but also reveals how hard it is to maintain privacy of individuals [18].

Privacy protection rules are also a challenge for data sets sharing within TEL. Especially, in the formal and workplace learning settings privacy protection rights hinder the exchange of these data sets.

Thus, before a data set can be shared, care must be taken to anonymise the data as much as possible. Individual user names should be anonymised so they cannot be traced back to their profile on the original Web 2.0 website, for instance by calculating a salted MD5 hash of the user name. It is important to keep in mind that with some dedicated investigation, even anonymised users and their items in the data set can often be matched to the data on the Web 2.0 website. These privacy concerns are also important when sharing results based on experiments with data collected from the Web. Although the recommendations are created for individual users and need to be as effective as possible for the target user, researchers should only report the general or aggregated effects of the recommender system over all or a group of users. Reporting about results of individual users and especially using their data as examples in publications could be understood as an attack on the privacy of a particular user. The APOSDLE project followed the approach of anonymising user names by mapping them to unique IDs. These IDs are then used throughout the system to link usage data to users. User details are stored in a separate system with limited access. Additionally, usage data could be encrypted before it is stored in a database, Although this approach is reasonable for enforcing privacy during runtime, it may not be appropriate for exporting data from a database to be used in a more or less publicly available data set. Without having access to encrypted usage data it is hardly possible to do any kind of comparison of recommender systems. Providing access to usage data may allow tracking back users by matching timestamps or usage data (e.g., performed tasks in APOSDLE) with other sources such as project management reports.

In order to overcome these challenges policies have to be created that protect the individual privacy and legal rights but enable also access to the data for research purposes and to develop recommender systems. For informal data sets the privacy rights might be less of an issue as they are mainly based on Web 2.0 data or open educational

resources that are already freely available on the Internet. But according to privacy policies, the owner of a data set has to explicitly agree with the contributors on the kind of processing that may be performed. Otherwise, the owner is not allowed to further process the data to achieve new insights. While data published on the Web is in the public domain, collecting it and sharing it by third parties is currently still a grey area with many different solutions. Addressing this issue is best done in collaboration with the data set provider that owns the original data. In the field of workplace-learning privacy issues could be addressed by following best-practice policies which have already been used in systems such as APOSDLE.

Privacy guidelines should be designed and comply with privacy directives such as the European Directive on data protection (95/46/EC). In addition, a classification of data sets into certain categories is needed to enhance an effortless sharing of data within a public data set collection. It is roughly thinkable to have public and private data sets. For public data sets no permission to view or use the data should be required. It would be possible to apply the Creative Commons protection rights as a standardised way to grant copyright permissions to the data sets. For private data sets users would need the permission of the creator or an organisation to get access and use a data set for their own research.

In addition, every owner of a data set should always have full control over the data when contributing it to a collection of data sets. Thus, the owner of a data set should be able to add or remove access of third parties to their own data set or remove the data set completely.

Finally, the policies should also clearly state how and when a reference to the data set needs to be made. For example, the original owner or creator of the data set should be acknowledged when a data set is used by other researchers.

5. Formats to exchange data sets

A well-defined format specification and description are inevitably when exchanging data sets between researchers. To define such a format it is important to agree on which kind of data is required to describe a recommender system and learning setting. In the following we discuss several aspects and propose a first format specification.

A representation of implicit or explicit feedback (explicitly by user ratings or tags and implicitly by click streams or time elapsed on pages) from the users regarding the candidate items is required by a recommender system to produce a recommendation.

This feedback can be in several forms. For example, in the case of collaborative filtering systems it can be ratings or votes (i.e., if an item has been purchased, viewed or bookmarked). In the case of content-based recommenders, it can be product reviews or simple tags (keywords) that users provide for items. Besides specifying how explicit feedback is encoded, format description must also contain details about how users (or their anonymised representations) are linked to feedback. The user-rating matrix used in collaborative filtering systems is a well-known example.

An important issue related to the representation and export of user feedback data sets from a given application environment is the declaration of the type(s) of feedback that is being collected and its format. For example, such an exported data set has to declare if the collected information is in the forms of ratings, reviews, or tags. In addition, it has to declare the exact structure and value spaces of the collected feedback. For instance, ratings may be collected upon one or more attributes (criteria), and using different rating scales. This can be particularly evident when examining evaluation or quality models for different application areas. In such a previous survey for TEL, Vuorikari et al. [19] found that rating learning resources takes place using a variety of review schemes or instruments.

To this end, an initial suggestion would be representing a data set using some plain and commonly acceptable format like comma-separated file formats (like CSV) or simple XML. To facilitate processing of similar information, we recommend that data sets that contain multiple types of social information or annotations (e.g., ratings, tags, textual reviews, bookmarks) are split up into different data set files, one file for each information type, e.g., the tags on the items, another file for the ratings, etc. Therefore, individual records in submitted files should at least include the following info:

- *userID*: ID of user providing the data (e.g., rating or tag). See note below on privacy.
- *itemID*: ID of the item that the data concerns (e.g., rating or tag)
- *content/value*: the actual data/info concerning the item (e.g., the text of the tag or the value of the rating)

In the case of multi-attribute data sets, files should include individual records that follow a similar format:

- *userID*: ID of user providing the data (e.g., rating or tag). See note below on privacy.
- *itemID*: ID of the item that the data concerns (e.g., rating or tag)
- *content/value of attr1*: the actual data/info concerning dimension/attribute #1 of the item (e.g., rating on dimension #1)
- *content/value of attrN*: the actual data/info concerning dimension/attribute #N of the item (e.g., rating on dimension #N)

Some general issues to consider include:

- additional information like timestamps could be included at the record level
- no data compression, encoding, or reduction should take place (apart from the elimination of blank or invalid values)
- user information should be anonymised (IDs should allow for distinguishing among users but should not reveal the true/real identifiers of the users or any other personal information)

In order to facilitate interoperability between different systems and potential reusability of exported user feedback in other application environments, it has been argued by Manouselis and Vuorikari [20] that it is important to define the particular social information scheme used. This means that apart from the data set files to be produced and shared, an accompanying description of the properties of the data sets is required,

The explanation of the attributes/dimensions should include a number of important attributes that will give enough information to a potential user of the data set for both the structure/format of the data set and the context in which it has been created/collected. To this end, such a description could include the following information about the submitted data set files; one table describing the data scheme used in each file (see Table 1).

Table 1. Example of a description of a rating scheme used when collecting a data set.

Example of Table: Rating Scheme used	
Element	Description
schemeID	example.com ratings
dimNum	1 (ratings are provided as total satisfaction)
Type	Rating
minVal	1
maxVal	5
stepVal	1 (rating is collected as integer)

- *schemeID*: title of data scheme used
- *dimNum*: number of dimensions that the scheme uses (useful when e.g., ratings use multiple dimensions / attributes)
- *Type*: type of data scheme in file (i.e. tag, rating values, textual reviews, bookmarks, and other)
- *minVal*: if applicable, minimum allowed value
- *maxVal*: if applicable, maximum allowed value
- *stepVal*: if applicable, rating/assessment scales intervals - for instance, step by which rating scale increases (e.g., if rating is an integer between 1..5, stepVal is 1)

For the overall data set (all files), information on the context in which the data set has been collected should be described.

- Application/environment: short description of the application in which the data set has been collected (e.g., Mendeley.com) and the relevant context (e.g., service/application provider, targeted users, educational setting, etc.).
- Data set contact: Currently responsible contact person with contact details (incl. institution and e-mail).
- Legal protection / open access policy: Is the data set available for public or does it require certain protection rules. In case it requires protection rules when and how it could be used by other researchers?
- Data set collection/processing method: How was the data set collected, which techniques have been applied to collect (e.g., logging users, storing user-provided info in system's DB), was the raw data set extended with additional information.
- Data set coverage (overall/instance): is the data set a complete reflection of the data in the system or just one instance of specific users or a given time period? Also define the sampling period and time (when and in which time period was the data set collected).
- Application/environment stats: total number of users, items, tags, ratings, reviews, etc. in the application (not the submitted data set but in total until date of reporting)
- Data set stats: number of submitted files, statistics per file (how many users, items, data entries per file), other meta-information.
- Raw or cleaned data set: Does the data set contain the original, 'raw' data or have certain noise reduction or stemming methods already been applied. If so, these pre-processing steps should be explained, as well as what part of the data.

Initial work on the development of a common metadata structure that will enable the representation, storage, sharing and reuse of such data sets has been carried out in the past [19][20]. Currently, this is a topic explored in the context of the STELLAR Theme Team on dataTEL^h as well as a Project Team on "An information model and its XML binding for capturing information about the perceived quality and (re)-usability of learning objects" of the Workshop on Learning Technologies (WS-LT) of the European Standardisation Committee (CEN). The two groups are in close communication and collaboration, and are expected to produce results of joint interest and agreement.

6. Conclusions

This paper has raised the issue of missing publicly available data sets in TEL that can be used as benchmarks to compare different recommendation systems. We discussed how suitable data sets could be created according to some initial guidelines, and investigated a number of steps that may be followed in order to develop reference data sets that can contribute to the scientific community. We discussed policies that are needed to enhance sharing of data sets by taking into account legal protection rights. Finally, an initial elaboration of a representation and exchange format for sharable TEL data sets was presented. In the following paragraph we discuss related challenges and future research needs.

Besides the sharing of data sets within TEL, another challenging issue is the creation of common evaluation criteria to compare the effects of TEL recommender systems. Consumer product recommendation systems are evaluated based on common technical measures like Accuracy, Recall, F1 and other performance indicator like

^h <http://www.teleurope.eu/pg/groups/9405/datatel/>

execution time in Adomavicius et al. [21]. But focusing only on technical measures for recommender systems in TEL without considering the actual needs and characteristics of the learners is questionable. In the literature there are two evaluation approaches to measure the impact of TEL recommender systems: a combined evaluation approach by Drachsler et al. [22] and a layered evaluation approach by Manouselis et al. [7]. They need to be explored further and perhaps combined to enable a standardised way of comparing TEL recommender systems.

Besides the selection of most suitable evaluation criteria another challenge is the creation of an overview of the performance of different TEL recommender systems. Therefore, already available data sets known from the TEL literature need to be combined in a collection and the applied recommender system and their outcomes should be described in relation to them. In that way, it could be monitored which and how certain recommender systems have been applied and what their outcomes were according to the standardised evaluation criteria. This would be a very helpful instrument for researchers to get an overview about applied recommendation approaches for different learning settings. The researchers could judge which recommendation approach performed better than others for a certain data set. It could be a first step forward to an evidence driven theory for recommender systems in TEL.

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